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A dynamic model for water management at the farm level integrating strategic, tactical and operational decisions

Marion Robert [a,*], Alban Thomas [b], Muddu Sekhar [c,d], Hélène Raynal [e], Éric Casellas [e], Pierre Casel [a], Patrick Chabrier [e], Alexandre Joannon [f], Jacques-Éric Bergez [a]

[a] INRA, Université Fédérale de Toulouse, UMR 1248 AGIR, F-31326 Castanet-Tolosan, France
[b] INRA, Toulouse School of Economics, UMR 1081 LERNA, F-31000 Toulouse, France
[c] Indian Institute of Sciences, Department of Civil Engineering, Bangalore 560012, India
[d] Indo-French Cell of Water Sciences, IRD-IISc, Bangalore, India
[e] INRA, UR 0875 MIAT, F-31326 Castanet-Tolosan, France
[f] INRA, UR 0980 SAD-PAYSAGE, F-35042 Rennes, France

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ABSTRACT

Farming systems are complex and have several dimensions that interact in a dynamic and continuous manner depending on farmers' management strategies. This complexity peaks in Indian semi-arid regions, where small farms encounter a highly competitive environment for markets and resources, especially unreliable access to water from rainfall and irrigation. NAMASTE, a dynamic computer model for water management at the farm level, was developed to reproduce interactions between decisions (investment and technical) and processes (resource management and biophysical) under scenarios of climate-change, socio-economic and water-management policies. The most relevant and novel aspects are i) system-based representation of farming systems, ii) description of dynamic processes via management flexibility and adaptation, iii) representation of farmers' decision-making processes at multiple temporal and spatial scales, iv) management of shared resources. NAMASTE's ability to simulate farmers' adaptive decision-making processes is illustrated by simulating a virtual Indian village composed of two virtual farms with access to groundwater.

1. Introduction

Agriculture faces many challenges regarding its productivity, revenue and environmental and health impacts, challenges that must be considered within the known context of climate change. Agriculture also faces demands to increase the quantity, quality, accessibility and availability of production to secure food production and improve product quality to address needs of the world's growing population (Meynard et al., 2012; Hertel, 2015; McKenzie and Williams, 2015). Agricultural productivity must increase within a framework of environmental and health concerns. To do so, agriculture should decrease its environmental impacts on water, air, soil and aquatic environments and consider the scarcity of resources such as water, phosphorus and fossil fuels (especially for production of nitrogen fertilizers) (FAO, 2011; Brown et al., 2015). Under climate change, warmer temperatures, changes in rainfall patterns and increased frequency of extreme weather are expected to occur. Consequently, it has direct, biophysical effects on agricultural production and can negatively affect crop yields and livestock (Nelson et al., 2014). Rising sea-level will increase risks of flooding of agricultural land in coastal regions, while changes in rainfall patterns could increase growth of weeds, pests and diseases (De Lapeyre de Bellaire et al., 2016).

On the Deccan Plateau in India, the countryside has witnessed the proliferation of individual, electrical pump-driven borewells that extract water from underground aquifers (Sekhar et al., 2006; Javeed et al., 2009). The low productivity of the aquifer (Dewandel et al., 2010; Perrin et al., 2011) and a rapid decline in the water table level has decreased borewell yields (Ruiz et al., 2015), indicating that (groundwater) irrigated agriculture still largely depends on rainfall. For a region that depends largely on monsoon and winter rainfall to maintain agricultural production, any shift in climate would have a severe impact on natural resources and the economy. Drilling borewells to gain control over water access

* Corresponding author.
E-mail address: m.robert.marion@gmail.com (M. Robert).

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is crucial to maintain household sustainability; however, it also entails the risk of failed borewells and intractable debts (Taylor, 2013).

Modeling and quantifying spatio-temporal variability in water resources and interactions among groundwater, agricultural practices and crop growth is an essential component of integrated and comprehensive water resource management (Ruiz et al., 2015). Simulating scenarios of climate change and water management policies is an essential tool to identify mechanisms that farmers can use and policies that can be implemented to address these challenges (White et al., 2015). In these modeling and simulation approaches, farmers' decision-making processes should be considered to assess how agricultural production systems change and adapt to external changes and opportunities. Farm management requires farmers to make a set of interconnected and successive decisions over time and at multiple spatial scales (Risbey et al., 1999; Le Gal et al., 2011). In the long term, farmers decide on possible investments and marketing strategies to select or adapt to best fulfill their objectives. Decisions about cropping systems also impact the farm. Decisions about crop rotation and allocation are considered at the whole-farm level (Detlefsen and Jensen, 2007; Castellazzi et al., 2008; Dury et al., 2010) and can be investigated in the long term and/or adapted for shorter periods. Once a crop is chosen, farmers must make (intra-) annual decisions to choose crop management techniques and the varieties to sow in the coming year. This decision can be made before cultivation and adapted, if necessary (tactical decisions). Generally, this decision concerns the whole farm to ensure that practices are consistent or to maintain a minimum of crop diversity on the farm. However, tactical decision descriptions are not sufficient to trigger daily operational management. Therefore farmers must define specific ways to execute their tactical plans. Farmers decide on crop operations and resource management and even change the purpose of their crops when conditions are not conducive to the initial plan. A farm decision-making model should include sequential aspects of the decision-making process and farmers' abilities to adapt and react (Akplogan, 2013). According to a review of modeling adaptive processes in farmers' decision-making (Robert et al., 2016a), 70% of the articles reviewed focused on only one stage of the decision: adaptation at the strategic level for the entire farm or at the tactical level for the farm or plot. We suggest reconsidering farm management as a decision-making process in which decisions and adaptations are made continuously and sequentially over time (the 3D approach: strategic Decisions/tactical Decisions/operational Decisions) to simulate reality more closely.

These considerations prompted the development of a simulation model able to reproduce interactions between decisions (investment and technical) and processes (resource management and biophysical) under scenarios of climate-change, socio-economic and water-management policies. This article presents this farming system model and an example of its application to a semi-arid region in Karnataka state, southwestern India. We first introduce the conceptual model and the modeling and simulation platform. We then describe the model – NAMASTE – in detail and illustrate its capabilities by applying it to a case study in southern India. Finally, we discuss the key modeling choices and present several insights on how to upscale the model from the farm level to watershed, regional and national levels.

2. Materials and methods

2.1. Conceptual modeling

We divided the systemic representation of the farming system into three interactive systems: i) decision system, which describes farmers' continuous and sequential decision process; ii) operating system (technical system), which translates decisions ordered by the decision system into instructions to execute tasks which is an action to perform on a biophysical object or location (e.g. sowing operation); and iii) biophysical system, which describes crop and soil dynamics and their interactions, especially relations between groundwater, soil, and plant development, using a crop model (Clouaire and Rellier, 2009; Le Gal et al., 2010; Dury, 2011; Akplogan, 2013; Robert et al., 2016b) (Fig. 1).

For the decision model, we consider farmers as cognitive agents able to think, memorize, analyze, predict, and learn to manage future events and plan their actions (Le Bars et al., 2005). In artificial intelligence and cognitive sciences, agents are commonly represented as Belief-Desire-Intention (BDI) agents (Bratman, 1987; Rao and Georgeff, 1991). The BDI framework is founded on the well-known theory of rational action in humans. BDI agents are considered to have an incomplete view of their environment (Simon, 1950; Cyert and March 1963). The concept of Belief represents a farmer's knowledge of the farming system and its environment. Desires are a farmer's objectives (goals that meet production or management goals). Intentions are action plans that achieve a farmer's objectives (Desires).

Farmers are represented as BDI agents at several levels of the conceptual model of the farming system. Farmers' beliefs and desires are the basis of the production processes in the farming systems. Farmers manage their farms based on their knowledge and objectives. Farmers have different types of knowledge about their farms: structural (i.e. farming structure and organization), procedural (i.e. know-how of farming practices), and observable (i.e. observations about their environment). Observing social and economic environments is important to be able to quickly respond to changes and uncertainties in the production context. The climate, prices of crops and inputs, and availability of external resources such as groundwater, labor or shared equipment are common uncontrollable data farmers use to make decisions. They also adapt their practices based on recent outputs of production systems, such as yields. Decision models provide the plans that farmers will execute in their production systems based on their observations and objectives, which translates into actions (invest, perform a crop operation, etc.) that correspond to intentions of the BDI agent. Contrary to these actions, which are direct outputs from the farmer decision-making model, other outputs are consequences of these actions on the biophysical system, such as impact on groundwater: water consumption due to the volume of water pumped and drainage due to the natural return of excess water from rainfall and irrigation (for more details, see Robert et al. (2016b)).

2.2. RECORD: a modeling and simulation computer platform

2.2.1. Overview

The RECORD platform is a modeling and simulation computer platform devoted to the study of agro-ecosystems (Bergez et al., 2013). RECORD facilitates design of simple single (atomic) or hierarchical complex (coupled) models and enables using different temporal and spatial scales within models. It is based on the Virtual Laboratory Environment (VLE), a free and open-source multi-modeling and simulation platform based on the Discrete Event System Specification (DEVS) formalism that derives from the theory defined by Zeigler et al. (2000) on modeling and simulation for dynamic systems with discrete events. VLE provides a simulation engine, modeling tools, software libraries, and an integrated development environment to the RECORD platform. Specific extensions have been developed in RECORD to bridge the gap

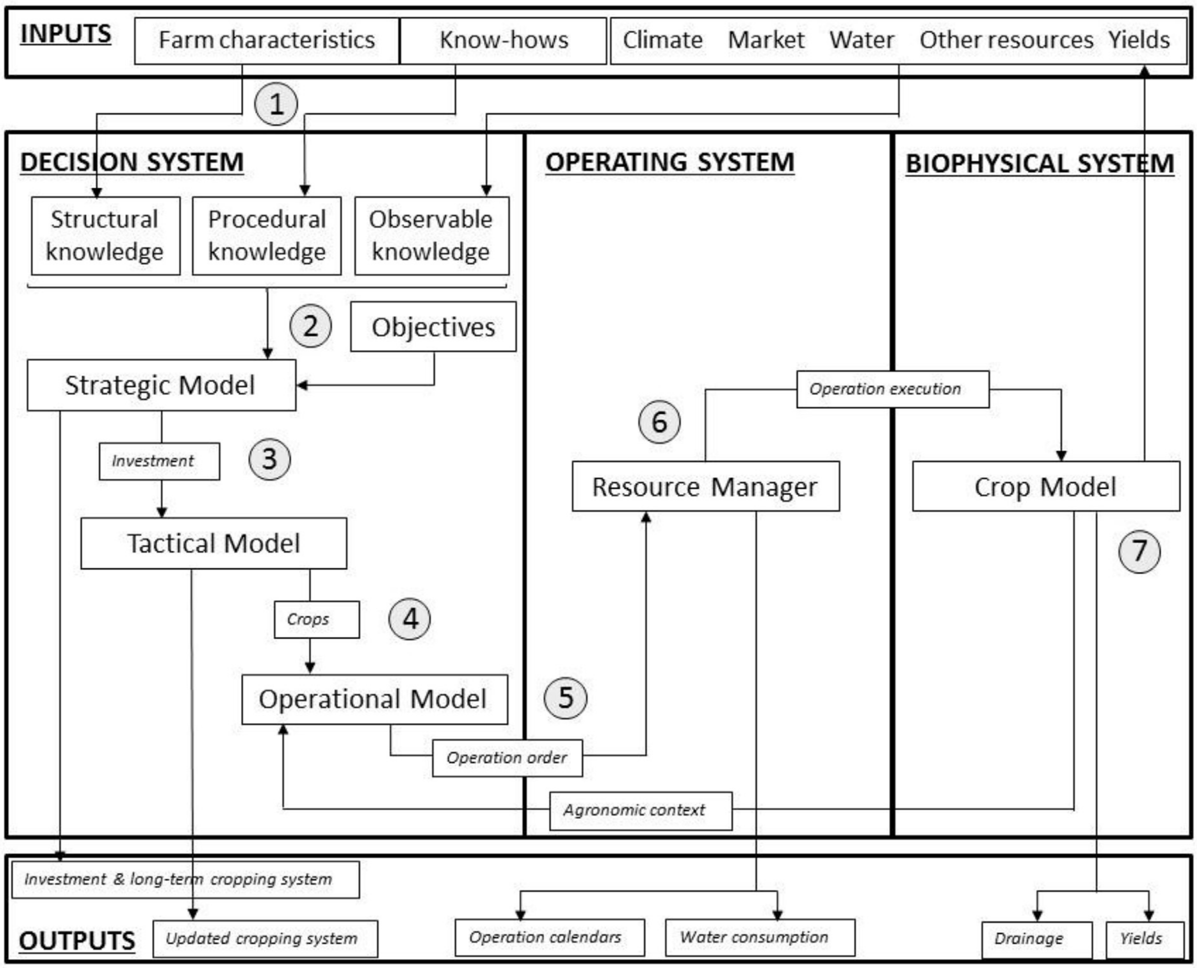


Fig. 1. Conceptual representation of the farming system based on integration of three systems. (1) The farmer uses information to make decisions. Information is described here as input to the decision system and can be from diverse forms (e.g. climate, water, market). From these information, the farmer is getting knowledge. The farmer has different types of knowledge: structural (i.e. farming structure and organization), procedural (i.e. know-how of farming practices), and observable (i.e. observations about their environment). (2) The Farmer manages his farm based on his knowledge and objectives and takes decisions; (3) the strategic model simulates the long-term decision-making process of the farmer resulting in investment and long-term cropping system decision. These decisions are the input used by the tactical model. (4) The tactical model describes the farmers' medium-term decision processes resulting in updating the cropping system based on the previous investment made. These updating decisions on cropping system are an input to the operational model. (5) The operational model describes short-term decision-making processes of the framer resulting in daily operation order to be executed at the field scale. (6) The operating system translates the operation orders into executable actions. These actions modify the state of the biophysical system. (7) The crop model simulates crop growth and water flow in the ground. Crop states, soil and water status are information observed by the farmer.

between the generic VLE and the framework adapted to the domain of agro-ecosystems. These extensions help modelers in developing their models in the formalism they are used or which is the most suitable by providing generic templates of codes and input parameters (see Bergez et al. (2013) for an extended description of the platform). In this study, two VLE extensions ("Decision" and "DifferenceEquation") were used to build the model, and a specific package (RVLE) for the statistical software R (R Core Team, 2016) was used to help perform simulations.

2.2.2. VLE extension "Decision"

To represent farmers' operational decision-making processes, the "Decision" extension (Bergez et al., 2016) implements the "decision" portion of the model in the "decision system/operating system/biophysical system" approach. During simulations, the decision model identifies the state of the environment (e.g. weather, plant, soil, resource availability) and sends orders to the connected models (e.g. a biophysical crop model) according to a flexible work plan of activities (i.e. the tasks to be achieved).

The work plan of activities contains the following:

i) a knowledge base composed of information about the system used to reach a decision. The information includes dynamics of biophysical processes, availabilities of human and material resources, and spatial information about farm structure. They are organized as a set of variables whose values evolve during the simulation to update the knowledge base at each time step.
ii) tasks to be executed and associated conditions (predicates, rules and time windows)
iii) temporal relations between tasks (for details of the "Decision" extension, see Bergez et al. (2016))

Recently, resource constraints were added to the conditions associated to the tasks. A set of available discrete resources is defined and structured by categories within the knowledge base. Resource constraints are defined for each task by a needed quantity, possible alternatives and priorities. During simulation, the resource

allocation is sequentially managed depending on resource availability and task priorities.

2.2.3. VLE extension "DifferenceEquation"

The VLE extension "DifferenceEquation" extension formulates time-discrete models that calculate values of real variables at time t as a function of the value of variables in the system at time t-Δ, t-2Δ, etc. (e.g. VarX(t+1) = f(VarX(t))). The expected parameters for an atomic model using "DifferenceEquation" are i) the simulation time-step (Δt), which must be the same for all equations; ii) the mode (either "name" of all external variables); and iii) the state variables and there initial values.

2.2.4. RVLE: a user-friendly tool in the RECORD platform

RVLE (www.vle-project.org) is an R package that calls VLE's application-programming interface from R. It can open packages and read model structure (VPZ files), assign experimental conditions to models, call the simulator, build experimental frames and turn simulation results into an R object such as a matrix or data-frame. It is especially useful for analyzing simulation results and performing statistics. It also allows users to manipulate models from the R environment.

3. Description of the farming system model

3.1. Models used to build the farming system model

3.1.1. The decision system

3.1.1.1. 3D: three integrated decision models. The novelty of the decision system is that three integrated decision models were built to represent farmers' strategic, tactical and operational decisions and adaptations. The strategic model simulates farmers' strategic decisions, which include decisions about investment and cropping systems. The tactical model simulates farmers' tactical decisions, especially adaptation of cropping systems. The operational model simulates farmers' operational and crop management decisions.

We used three modeling formalisms to describe farmers' decisions throughout the decision process. Decisions about investment and cropping systems that are influenced by economic return (maximizing profit) were expressed using dynamic stochastic programming. Decisions about establishing cropping systems that are influenced by motivations besides economic return (e.g. proximity to a market, equipment) were implemented via a decision-rule modeling approach using a specific descriptive language whose syntax is based on formal IF-THEN-ELSE rules written as a Boolean condition: "IF<*indicator*><*operator*><*threshold*> THEN <*action1*> ELSE <*action2*>". Decisions about crop management were described as an activity graph supported by the "Decision" extension in the RECORD platform and using a knowledge base. The knowledge base collects information that the farmer obtains from the biophysical subsystem when monitoring and observing the environment. The activity graph represents the farmer's work plan and relies on the knowledge base to activate or disable technical operations. An activity denotes a task. Rules control the start of the activity by checking whether conditions necessary to perform the operation exist (for details of this formalism, see Bergez et al. (2016)).

3.1.1.2. Modeling resource management in the operational decision model. From a modeling viewpoint, two types of resources were distinguished in the farming system: i) conditional, discrete and returnable resources, which are necessary to execute an operation and can be used and then returned once the operation is finished (e.g. labor, tractor); and ii) unconditional and consumable resources, which are not necessary to execute an operation and are consumed and not returned after use in an operation (e.g. irrigation water). These resources are managed differently in the model. The operating system manages the unconditional and consumable resources. For example, following an order to execute irrigation, the decision system returns each day the amount of water needed to irrigate the farm. The operating system compares the water needed to the water available and executes the order to irrigate by transferring the lesser of the two values (water needed or water available) to the biophysical system.

Conflicts between activities requiring the same conditional, discrete and retrunables resources at the same time are dynamically managed using rules to allocate resources and determine the order in which activities are executed. Prioritization is managed by rules that temporally rank activities that can be executed simultaneously. Ranks can be reviewed and updated by other rules.

3.1.2. The operating system

The operating system translates decision orders into executable and timed actions. It calculates the duration of each activity based on the quantity and type of resources that an operation uses and the speed with which each resource executes an operation (entered in the experimental conditions of the simulation). The operating system can also transform certain data transferred from the decision system so that data units correspond to those expected by the receiving model. The operating system is implemented using difference equations in RECORD.

3.1.3. The biophysical model

The STICS model, which represents the crop and soil system, simulates dynamics of a crop-soil system over one or more crop cycles at a daily time-step (Brisson et al., 1998). We selected STICS for its adaptability to many crop types, robustness in a wide range of soil and climate conditions and modularity (Brisson et al., 2003). It has been successfully used in spatially explicit applications and coupled with hydrological models at the watershed level (Beaujouan et al., 2001). STICS receives the crop operations and parameters applied to the plot from the operating system, which executes orders provided by the decision system. STICS returns information about crop stage, yield, soil characteristics, water use and drainage. The FORTRAN code in STICS was wrapped into an atomic model using difference equations in RECORD (Bergez et al., 2014).

3.2. Model structure

The model is composed of one decision system and one operating system, the latter of which interacts with one biophysical system (Fig. 1). The biophysical system can be made up of several crop models. For example, an independent STICS model represents the crop and soil of each plot of the modeled farm. For each plot, the decision system has a work plan with specific activities listed for the plot's crop. Several work plans may run in parallel when the modeled farm has several plots.

The resource manager must manage conditional, discrete and returnable resources both among activities in a given work plan and among work plans. In this case, prioritization is used to rank all activities temporally. Unconditional and consumable resources are distributed by an intermediary model that, for example, allocates irrigation water to plots when the decision system sends several irrigation orders on the same day. Available water is distributed according to priorities assigned to work plans. To simulate the cropping system over several years, several work plans for the same plot must be run sequentially; the next one is loaded when the last activity of a given work plan is completed.

3.3. Dynamic functioning

In systemic modeling, (i.e. modeling a complex system as subsystems interacting with each other) models must be able to interact with each other to provide feedback and other types of interactions. Two types of variables are identified in models: state variables, which are managed by the model itself, and external variables, which are managed by other models.

External events (e.g. rainfall, market prices, electricity availability) and availability of resources (e.g. labor, equipment, irrigation water) are summarized in the INPUTS model (Fig. 1).

At the beginning of the year, the strategic model receives information from INPUTS so that strategic decisions about investment and long-term cropping systems are based on farmers' knowledge and objectives. These two types of strategic decisions are forwarded to the tactical model,. At the beginning of the cropping season, the tactical model receives information from INPUTS so that farmers' knowledge is updated. This new information prompts the tactical model to update the cropping system and forward the adapted cropping system to the operational model. At the operational level, decisions are based on the appropriate agronomic context and the farmers' updated knowledge. Once both types of information meet the requirements for executing an operation and are forwarded to the operational model, an operation order is transferred to the operating system, which translates it into a task execution so that the operation is performed in the plot one day after the decision is made. At the end of the operation, the crop model returns the agronomic context to the operational model. After harvest, the operational model informs the tactical model that the cropping season is over. When the tactical model automatically wakes up on day 250 (official end of the season), it receives information about the successful harvest and updated knowledge about the system, processes and updates the cropping system for the second season and forwards this updated cropping system to the operational model. At the end of the second season, the same process occurs, and soon after the second year begins.

4. Application case: the NAMASTE simulation model

NAMASTE simulates farmers' adaptations to uncertain events such as climate change, water table depletion, the economic environment and agricultural reforms. We applied NAMASTE to a case study located in Karnataka state, India, in the Berambadi watershed. The cropping system is organized around three seasons: i) the rainy season (kharif), when most crops are grown; ii) the winter season (rabi), when mainly irrigated crops are grown and iii) the dry season, when little cultivation occurs (summer). Monsoon rainfall is a key determinant of crop choice. Farmers make three types of decisions: i) whether to invest in an irrigation system, ii) crop selection and iii) crop management and operations. All farmers in the watershed pump irrigation water from the same aquifer, and those from the same village share labor and equipment.

To illustrate NAMASTE's ability to simulate farmers' adaptive decision-making processes under conditions of both limited and shared resources, we ran a baseline scenario over a 10-year planning horizon in which the parameters that describe the climate, crop market conditions (prices and costs), and water pumping conditions (i.e. hours of electricity available each day, cost of pumping) were based on those obtained from farmer surveys.

4.1. Coupling the farming system model to the hydrological model

Rainfall, market prices, and availability of electricity, labor, equipment, and irrigation water are inputs to the farming system. They are modeled as subsystems of an external system that limits the farming system (Fig. 2).

4.1.1. Hydrological subsystem

AMBHAS (Tomer, 2012) is a spatially explicit groundwater model that simulates dynamics of daily groundwater level based on equations from McDonald and Harbaugh (1988). It predicts daily groundwater level, actual net recharge and discharge. For a 1 ha cell, the net recharge is calculated as the difference between the amount of water drained below the soil profile and the required water amount for crop irrigation predicted by STICS. As for the STICS model, a wrapper was used to integrate the AMBHAS code into RECORD avoiding heavy recoding. This wrapper was based on difference equations formalism.

4.1.2. Climate, market and power supply subsystems

The WEATHER model simulates expected and actual rainfall each day. The MARKET model simulates expected and actual crop market prices. The ELECTRICITY model simulates the number of hours of electricity available each day. These sub-models are implemented in an atomic model using difference equations in RECORD.

4.2. NAMASTE simulation

When resources are shared, interactions are important to an individual farmer's decision-making process. To integrate resource constraints into the farming system model, our experimental model simulates a virtual village composed of two virtual farms that have access to groundwater in the same AMBHAS cell of 3 ha (Fig. 2). The first farmer manages 1 ha of land organized into two crop plots and owns one bullock for cropping operations; the second manages 2 ha of land organized into two crop plots and owns two bullocks. Neither farmer owns a tractor. On each farm, both the farmer and his wife work. Both farms can hire labor and rent equipment from the village (i.e. 50 female laborers, 40 male laborers, 4 pairs of bullocks, 1 tractor). Because a borewell can be drilled on each plot, this NAMASTE simulation consisted of four borewell models. During simulation, the strategic decision model may change the parameters for pump horsepower and well depth. The net recharge (water drained minus water pumped) returned to the AMBHAS cell is calculated by an intermediate model that calculates the difference between total drainage and pumping flows of all plots.

NAMASTE simulation of two farms in one village proceeds as follows. Each farm is simulated by a decision system, which includes strategic, tactical and operational decision models. NAMASTE considers farm characteristics (e.g. number of plots, soil type, amount of labor and equipment), crop management files and initial farm status as initial conditions. The operational decision model manages the village's labor and equipment that is used for crop production. It functions as a resource manager and attributes resources to the first enquirer. The operational model interacts with the operating system, while the biophysical system has as many STICS models as there are plots in the village. The external system (i.e. WEATHER, MARKET and ELECTRICITY models) constrains both farms in the same way, and we assume that farmers' individual or combined decisions do not influence it. The same AMBHAS cell simulates the irrigation water available to both farms.

At the beginning of the year, in the strategic model, each farmer makes decisions about investment and the cropping system for the next ten years independent of other farm decisions. Investment in a borewell determines parameters of the borewell model for each plot. At the beginning of the cropping season, in the tactical model, each farmer independently updates the cropping system based on

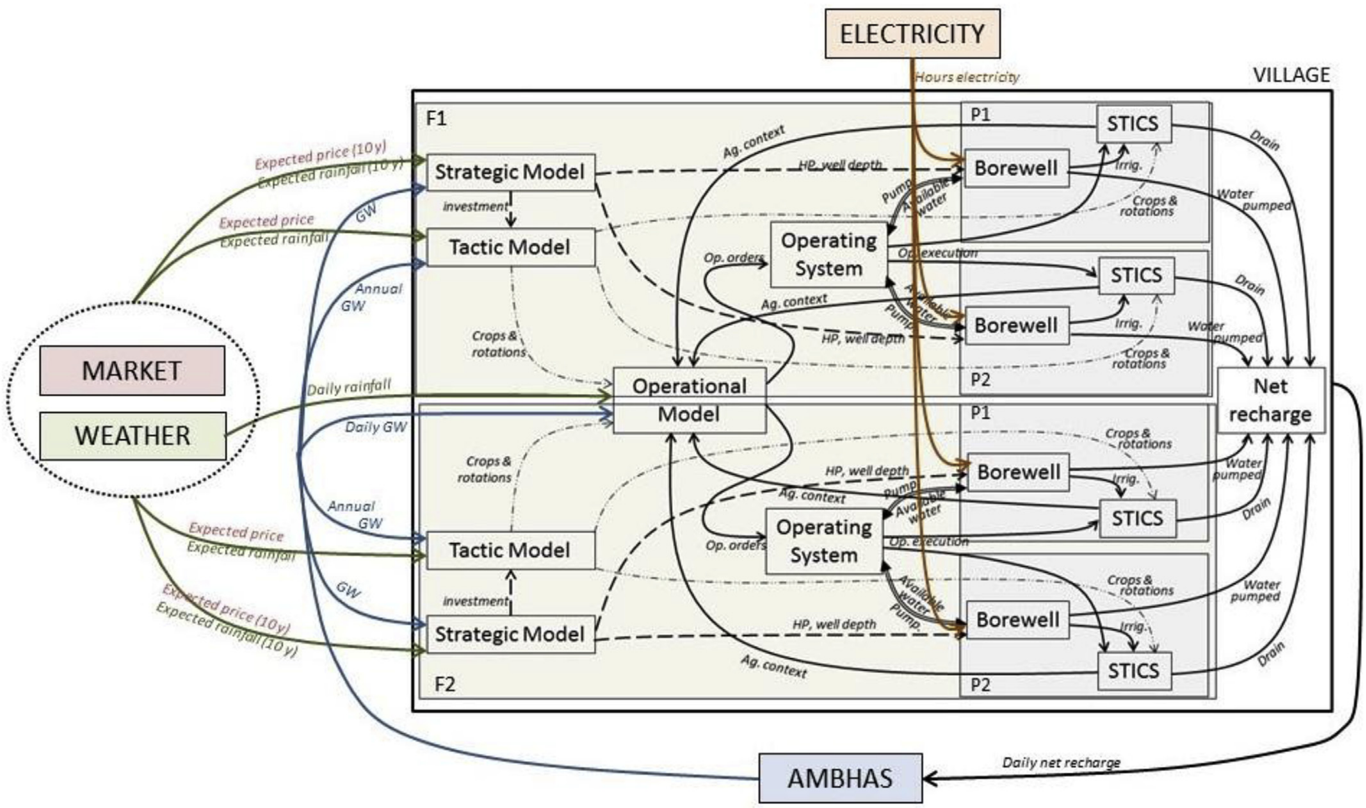


Fig. 2. NAMASTE model: a virtual village composed of two virtual farms, each having access to ground water on the same AMBHAS cell. Each farm is simulated by two individual DEVS atomic decision model (strategic and tactic) and a common operational decision model using the VLE decision extension of RECORD that describes individual operational decisions for the whole village. The WEATHER model, the MARKET model and the ELECTRICITY model are constraining the same way both farms. Farm 1 (F1) contains two plots P1 and P2, Farm 2 (F2) contains two plots P1 and P2. The arrows mean:
— — →Information flux exchanged at the strategic level: the strategic model provides decision on investment in irrigation which lead to the addition (when investment is decided) of a borewell model (with specific characteristics such as the horsepower (HP) and the well depth). Strategic decisions depend on observation made on market and weather environment (expected prices and rainfalls for the 10 coming years) and on expected groundwater level (GW).
- · - · - →Information flux exchanged at the tactical level: the tactic model updates the cropping system at fixed investment in irrigation (information coming from the strategic model) and send information to the STICS model that load several work plans for the same plot so that work plans are run sequentially. Updated cropping systems are sent to the tactic model. Tactic decisions depend on observation made on market and weather environment (expected prices and rainfalls for the coming year) and on expected groundwater level (GW).
———→Information flux exchanged at the operational level: based on crop choices made at the tactical level and on observation on daily rainfall and daily groundwater level (GW) as well as on observations on the agricultural context (Ag. Context from the biophysical system STICS), the operational model sends operating orders (Op. orders) to the operating system that translates these orders into operation execution (action = Op. execution). For irrigation order, the operating system is considering the available water from the borewell to compare the available water to the expected irrigation volume and estimate the real irrigation volume that can be provided to the biophysical system (pump). STICS return the drained water, the BOREWELL model returns the water pumped so that the net recharge of the groundwater is estimated and returns as daily net recharge to the AMBHAS model.

new information on prices, rainfall and groundwater level. This updated cropping system is then entered into the operational model, which defines the crop rotation and the management of each crop. The operational model determines when conditions necessary for crop operations are met and requests resources from its resource manager. Farmers' practices interact at this level, which means that one farmer's crop operations may be restricted by the other's when both need labor and equipment at the same time. Irrigation water may also be a source of conflict between farmers, since the water that one farmer withdraws from the aquifer is no longer available to the other (Fig. 2).

4.3. Calibration and validation

The model was calibrated with data from two farm surveys conducted in the Berambadi watershed. Farmers on the watershed were surveyed in 2014 and 2015. The first survey targeted 27 farmers to obtain detailed data about their practices, especially their decisions and how they adapted them. The second survey targeted 684 farmers to obtain broad data on farm characteristics and the social, economic and agronomic environments. This survey enabled creation of a typology of farmers on the watershed based on biophysical factors (e.g. farm location, soil type, groundwater accessibility), economic factors (e.g. farm size, labor, equipment) and social factors (e.g. castes, family structure, education, off-farm job) (for more details, see Robert et al. (2017a)). We surveyed seed retailers and village leaders (panchayats) to learn about recommended crop management practices and village organization. Additionally, 52 experimental plots were monitored over three years, which provided empirical data on crop production and management. These data helped supplement the verbal information that farmers provided during surveys. Meteorological data were obtained from a meteorological station and water gauges installed on the watershed. Prices and costs were obtained from farmers and official district data from the Indian Ministry of Agriculture and Cooperation (Directorate of Economics and Statistics) and the National Informatics Center (Agricultural Census Division).

The model was validated using computerized model verification

and operational validation. Computerized model verification checks whether the computer implementation corresponds to the conceptual model representation (Whitner and Balci, 1986; Sargent, 2013). It verifies that the computer code has no coding errors or computer bugs and that the simulation language is implemented well. We used two main approaches for computerized model verification: i) static, which tests the main script at multiple points, allowing for local checks during encoding, and ii) dynamic, which executes the script with several sets of data and experimental conditions to verify the accuracy of outputs. In contrast, operational validation checks whether the behavior of the final simulation model is accurate enough to fulfill the research objectives. The model was validated mainly by subjectively exploring its behavior (Sargent, 2013) and graphically comparing model predictions to observed data, verifying that predicted yields lay within the ranges of observed yields in the watershed (details not shown). The crop model STICS was validated using plot data (Sreelash et al., 2017). The AMBHAS model was validated on watershed data (Tomer, 2012). We also qualitatively analyzed model behavior, verifying that predicted variables moved in the same directions as observed variables. For example, we verified that crop choice, management and yield correctly responded to climate variations; that investment in irrigation corresponded to economic and climate environments; and that the groundwater table correctly responded to rainfall and irrigation.

4.4. Simulation results

4.4.1. Sequential decision making and adaptation at different temporal and spatial scales

To illustrate decision processes and adaptations, we describe the sequential decision-making processes the first farmer followed to cultivate 1 ha of land. In long-term decision-making, the farmer's objective is to select the sequence of investment in irrigation equipment and season-specific crops that maximizes the discounted stream of future revenue across the 10-year planning horizon. Such selection is based on expected rainfall and crop prices, and available water for irrigation. At the beginning of the 10-year planning horizon, the farmer has expectations for the future climate (i.e. percentage chances that a year will have good (2.4%), above-average (22%), average (46%), below-average (22%) or poor rainfall (7.3%)) and decides in the sequence of investment in irrigation equipment and season-specific crops he should do to maximize his future revenue across the 10-year planning horizon. Running the strategic decision model at the beginning of the 10-year planning horizon results in one investment in irrigation equipment (dig a borewell the first year) and a 10-year cropping system described in the first column of Fig. 3. As time passed, the farmer is receiving new information on his environment and is observing changes in the weather conditions. In fact, his expectations on climate may evolve as time passed and he may review and update his weather expectation at the beginning of each year or even each season compared to his expectations at the beginning of the planning horizon. For instance, comparing weather expectations used in the strategic decision model and those used in each run of the tactical model results in going from percentage chances that a year will have good (2.4%), above-average (22%), average (46%), below-average (22%) or poor rainfall (7.3%) to the yearly belief that the first year will be average rain, the second year will be average rain, the third year will be above average rain, the fourth year will be below average rain, the fifth year will be average rain, the sixth year will be above average rain, the seventh year will be average rain, the eighth year will be average rain, the ninth year will be poor rain and the tenth year will be below average rain. In the

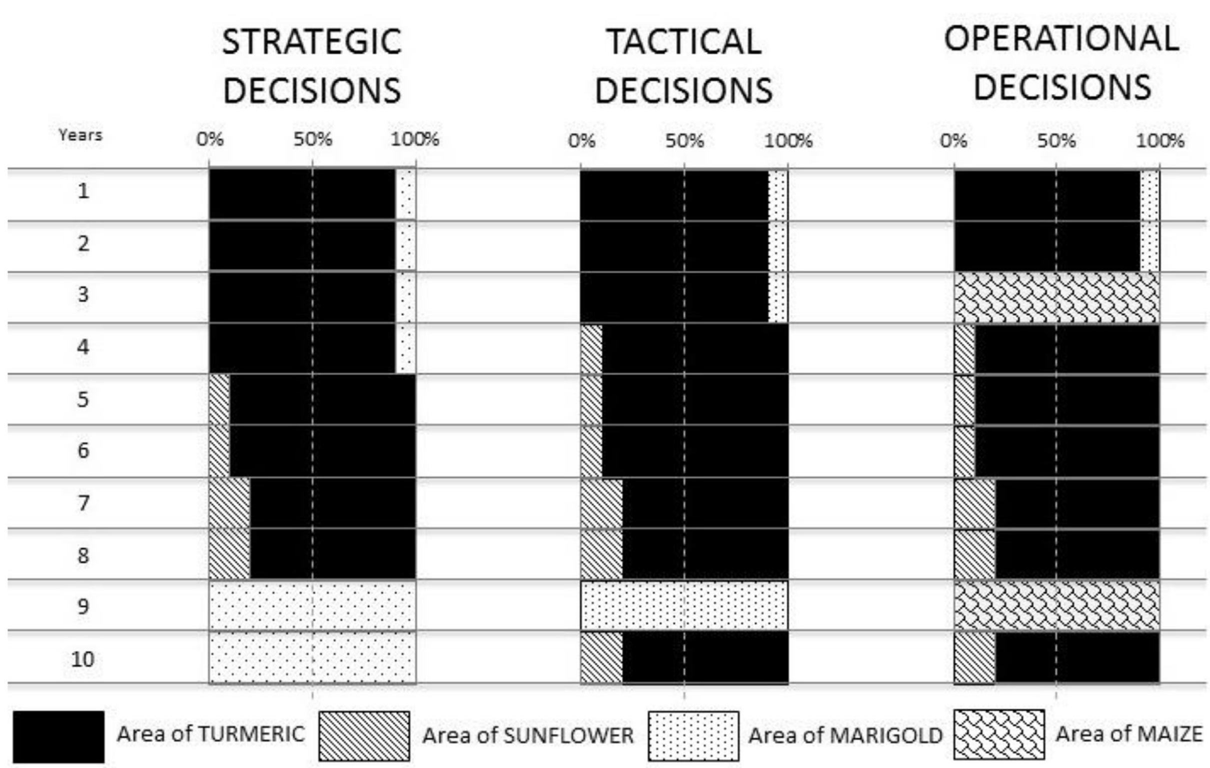


Fig. 3. Decisions and adaptations of the cropping system of one farmer during the 10-year planning horizon (each line describes one year). The first column describes the farmer's strategic decisions on cropping system. The second column describes the farmer's tactical decisions and adaptations at the beginning of each year after observing the weather and the groundwater level. The third column describes the farmer's operational decisions and adaptations of crop choice after observing daily rainfall.

computations and the simulations, rainfall selection within the tactical decision model is made by using probability of occurrence used in the strategic decision model updated accordingly with daily rainfall provided by the weather model. In medium-term decision-making, the farmer's objective is to review the season-specific crops that maximizes the future revenue that should be obtained at the end of the year. Running the tactical decision model at the beginning of each year (10 runs) results in yearly updated cropping systems described in the second column of Fig. 3. At the tactical level, the farmer knows what kind of climate to expect (i.e. average rainfall) but is uncertain about the seasonal distribution of rainfall throughout the year. By starting daily crop operations (operational decisions), the farmer can adapt crops and/or practices when conditions are not suitable. Thus, the crop that will finally be harvested at the end of the season by the farmer (third column of Fig. 3) may be different from the one selected at the beginning of the year (tactical decisions, second column of Fig. 3) and at the beginning of the planning horizon (strategic decisions, first column of Fig. 3).

Changes in rainfall expectation and cropping system choice led the farmers to review his expectations on the groundwater level and profit (Fig. 4). Expected profit in long- and medium-term are computed based on crop prices, expected yields, irrigation costs and other crop-specific costs (investment in irrigation equipment are included in the long-term profit expectation computation) (details are provided in Robert et al., 2017b). Expectations on groundwater level are necessary in particular for the long-term decision since the decision on investment in irrigation will impact on future access to irrigation water. Expectations on groundwater level are also necessary on medium- and short-term decisions, since pumping water and irrigating a crop will impact on the future availability of irrigation water. Long- and medium-term groundwater level expectations depend on borewell recharge from rainfall, borewell discharge, water pumped for irrigation the past period and the capital stock depreciation rate of the equipment (details are provided in Robert et al., 2017b). Note that short-term groundwater expectations are replaced in the computations and the simulations by observed groundwater level from the groundwater model.

Tactical and operational adaptations influenced the groundwater level and the farmer's profit (Fig. 4). Due to generally adequate rainfall during the planning horizon (except the 4th, 9th and 10th years), pumping was lower and recharge was higher than predicted at the strategic level. Thus, the groundwater level did not decrease as much as expected, and the borewell did not go dry during the planning horizon. Concerning profit, rainfall induced economically disastrous years (i.e. 3rd and 9th years), by preventing the farmer's initial cropping system plan and requiring maize to be sown, or highly profitable years (i.e. the 6th year), by being above average and well distributed during crop growth. In at least one year (i.e. the 10th) irrigation was able to compensate for the below-average rainfall and provide a profit.

The fourth year illustrates crop choice adaptation at the tactical level. At the beginning of year 4th, the farmer is convinced the season will be below-average rainfall. The farmer, knowing that low rainfall during the cropping season impacts rainfed crops in particular and observing a groundwater level much higher (12.4 m higher) than expected at the beginning of the planning horizon (Fig. 4), changed 0.1 ha of rainfed marigold to irrigated sunflower (to go with the 0.9 ha of irrigated turmeric) (Fig. 3).

The third year illustrates crop choice adaptation at the operational level. The farmer planned to grow 0.9 ha of turmeric and 0.1 ha of marigold. Both crops have similar sowing windows (30 March−1 May) and conditions (rules): soil moisture must be low enough to bear loads (rule: < 75% of field capacity) but high enough for seeds to germinate (rule: > 60% of field capacity) and rain must not be forecast for two consecutive days (since sowing can last two days) (rule: total expected rainfall for two consecutive days must not exceed 5 mm). Five days in April (6, 7, 8, 9 and 11) had acceptable soil moisture (60-75% of field capacity), but April's high rainfall (147 mm) prevented sowing. Because sowing turmeric and marigold was not possible, the farmer had to review the cropping plan and sow only maize, which has a wider sowing window (April -June).

The sixth year illustrates practices adaptation at the operational level. Unlike in the third year, turmeric and sunflower could be sown in April; however, frequent rainfall events after sowing decreased the number of irrigation events planned for turmeric. Four planned irrigation events were cancelled because irrigation rules recommend irrigating when total rainfall during the past three days is < 50 mm and <5 mm of rainfall is expected in the next two days.

4.4.2. *Resource management: between scarcity and sharing*

NAMASTE considers situations in which resources may be limited because they are scarce and limited and/or used by another farmer. In these conditions, farmers adapt their daily practices, delaying crop operations until resources become available. Competition for resources can be internal, when operations occur at the same time in two plots of the same farm, or external, when competition is due to another farmer's practices.

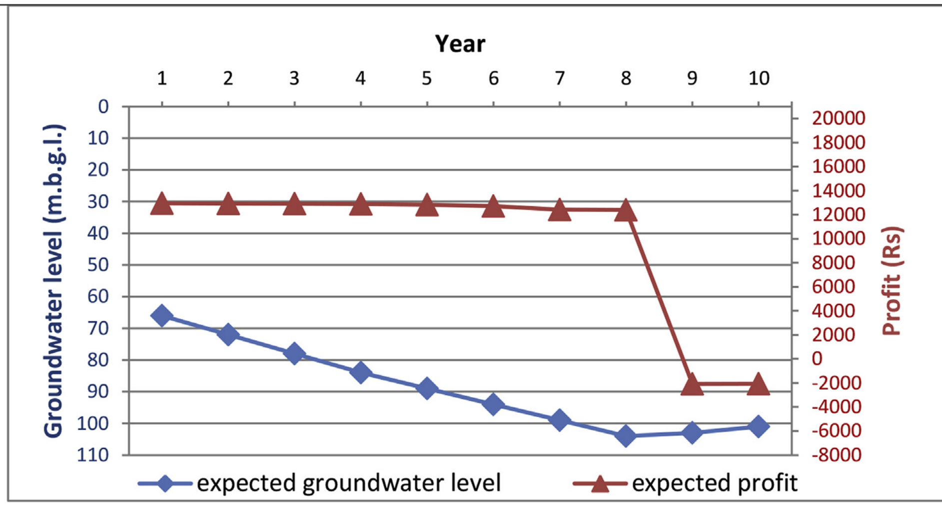
To illustrate resource management in NAMASTE, we describe management of village resources (50 female laborers, 40 male laborers, 4 pairs of bullocks, 1 tractor) in the first year of the planning horizon (Fig. 5). The first farmer planned to grow turmeric on 0.9 ha with 16 irrigation events and rainfed marigold on 0.1 ha. The second farmer planned to grow turmeric on 1.6 ha with 12 irrigation events and rainfed marigold on 0.4 ha. Three types of resource conflicts were observed (Table 1 and Fig. 5):

4.4.2.1. Type 1: conflicts over use of the tractor to plow land. Turmeric and marigold plots must be plowed during the same window (1-23 March) and according to the same conditions (rules). Since turmeric has a higher priority index than marigold (i.e. the farmer prefers economically to grow turmeric than marigold), the resource manager allocates the tractor to the turmeric plots first (e.g. the first tractor plowing occurs on 10th-11th March for turmeric plots and 15th -16th March for marigold plots). Between turmeric plots, the resource is randomly attributed. For example, for turmeric, the first tractor plowing occurs on March 10th on farm 1 and March 11th on farm 2 and the second tractor plowing occurs on March 20th on farm 1 and on March 21st on farm 2.

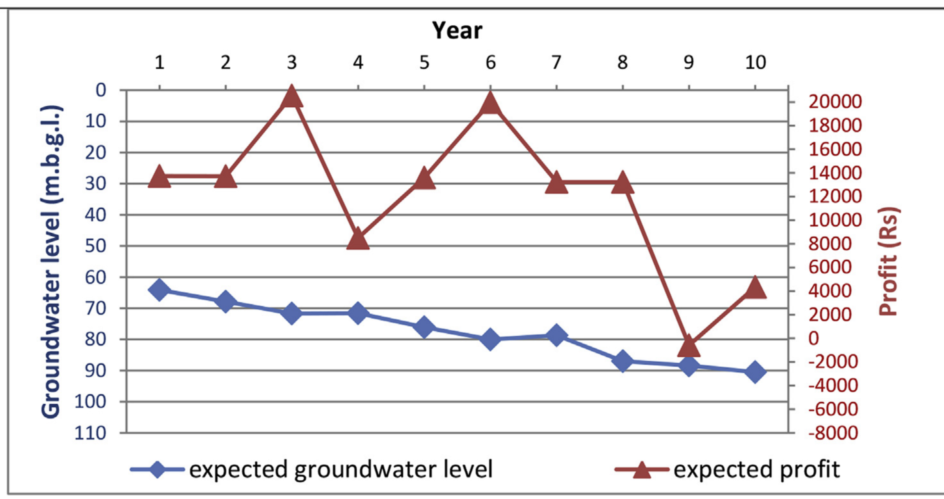
4.4.2.2. Type 2: conflicts over use of female labor to weed turmeric. Since both turmeric plots were sown on the 13th of April, they had the same time windows for weeding events (10-35, 55-65, 85-95 and 115-125 days after sowing). For each weeding event, the first farmer needed 28 male and 21 female laborers, and the second farmer needed 14 male and 37 female laborers. Since the village had only 50 female laborers, both farmers could not weed their plots at the same time. The resource is randomly attributed.

4.4.2.3. Type 3: conflicts over use of both female and male labor to harvest turmeric. The first farmer needed 20 male and 23 female laborers, and the second farmer needed 35 male and 42 female laborers to harvest their turmeric plots. Since both female and male labor was limited at 50 and 40 laborers respectively, one of the farmers had to delay harvest.

A) Groundwater level and profit expectations used for strategic decision-making made at the beginning of the planning horizon



B) Groundwater level and profit expectations used for tactical decision-making made at the beginning of each year



C) Groundwater level and profit observed at the beginning of each year after daily cropping operations

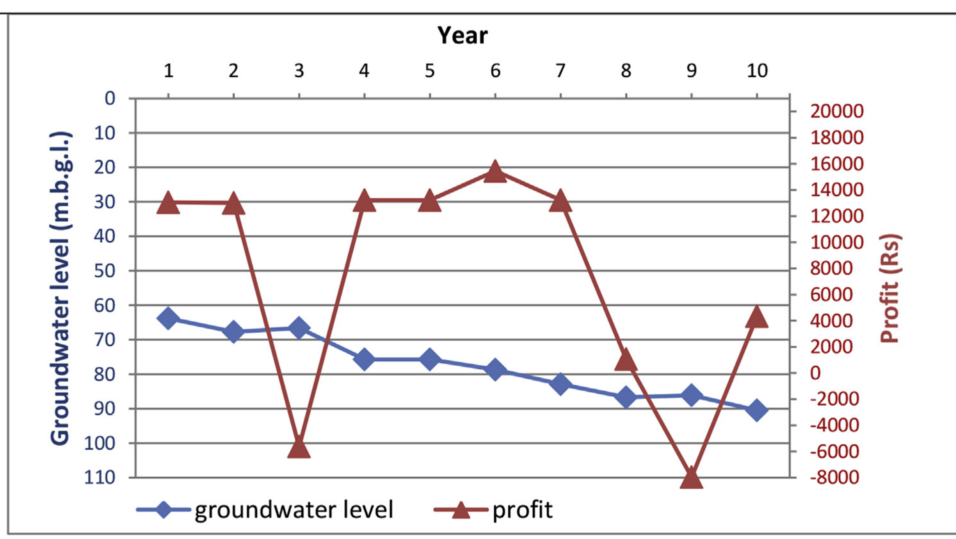


Fig. 4. A) Groundwater level and profit expectations used for strategic decision-making made at the beginning of the planning horizon; B) Groundwater level and profit expectations used for tactical decision-making made at the beginning of each year; C) Groundwater level and profit observed at the beginning of each year after daily cropping operations.

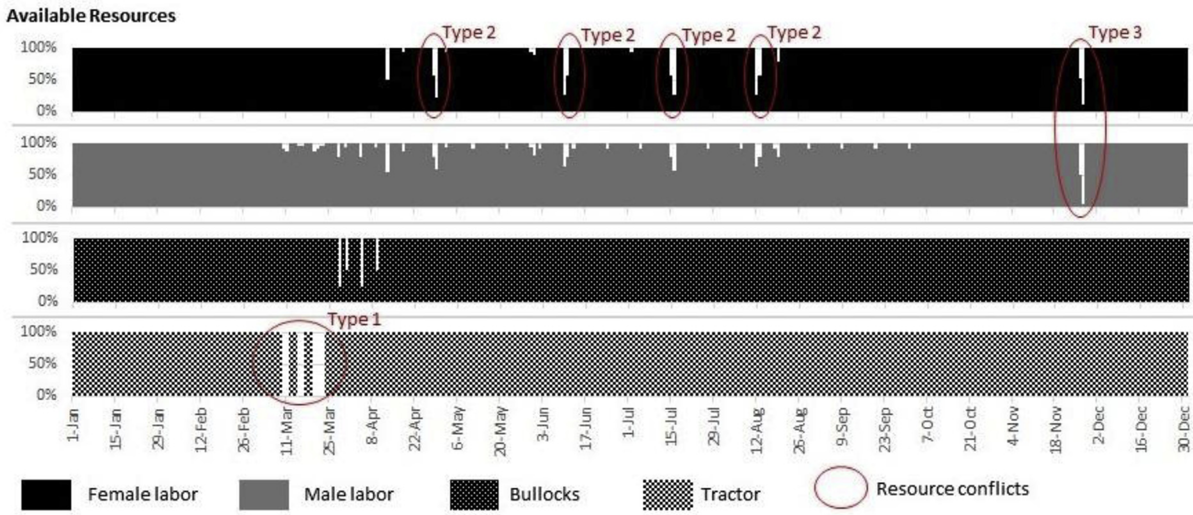


Fig. 5. Resource management in a village composed of two farms – example of available (in %) village resources (female and male labor, bullocks and tractor) during the first year of the planning horizon. Three conflicts are identified (1, 2, 3). Activities of one farm were postponed when resource conflicts occurred.

5. Discussion

Understanding farmers' decision-making processes and relationships with the biophysical system is necessary to understand farming system complexity at multiple scales. NAMASTE is a model able to simulate decision-making processes and interactions between strategic, tactic and operational decisions (investment, cropping system and technical) and processes (resource management and biophysical) under scenarios of climate-change, socio-economic and water-management policies. The model proposes two main innovations: i) its decision model simulates farmers' decision-making processes by describing dynamic sequential decisions via adaptation to the biophysical environment and ii) it couples decision, economic, biophysical and hydrological systems through an integrative approach to predict effects and spillover of human decisions on natural systems.

Research increasingly considers farm management as a flexible and dynamic process. In recent agricultural literature, however, consequences on long- and short-term farm organization are rarely considered, even though they appear to influence farmers' decision-making greatly (Daydé et al., 2014). Indeed, 70% of the articles reviewed in Robert et al. (2016a) focused on only one stage of the decision: adaptation at the strategic level for the entire farm or at the tactical level for the farm or plot. Some authors combined strategic and tactical decisions to consider the entire decision-making process and adaptation of farmers. Dynamic programming is a dynamic model that allows the adaptation of strategic decisions according to adaptations made to tactical decisions. It has been used to address strategic investment decisions (Reynaud, 2009; Duffy and Taylor, 1993) and to address tactic decisions about cropping systems (Hyytiäinen et al. (2011); Thomas, 2003). Other authors combined reactive formalisms with a recursive approach and static discrete stochastic programming approaches to describe the sequential decision-making process from strategic decisions and adaptations to tactical decisions and adaptations (Mosnier et al., 2009; Belhouchette et al., 2004; Lescot et al., 2011). We used the basic definition of Le Gal et al. (2011), which divides a decision into a set of interconnected decisions made over time and at multiple spatial scales. Sequential and dynamic representation is particularly useful and appropriate for modeling entire processes for making strategic, tactical and operational decisions (Risbey et al., 1999; Le Gal et al., 2011). We proposed in this paper to combine several formalisms within an integrated model in which strategic and tactical adaptations and decisions influence each other to model adaptive behavior within farmers' decision-making processes. To model three stages of decision, we combined economic, decision-rule, and activity-based models.

The integrative approach of coupling decision, economic, biophysical and hydrological models was necessary to model and quantify spatio-temporal variability in water resources and interactions among groundwater, agricultural practices and crop growth. One difficulty in modeling these processes is combining independent models that were originally developed for specific purposes at different spatial and temporal scales (Kraucunas et al., 2015). The biophysical model used in NAMASTE was developed to simulate fixed practices such as sowing, irrigation and harvest on one plot for one cropping season (see Brisson et al. (1998) for more details on the STICS model). The hydrological model simulates groundwater dynamics of a large territory (see Tomer (2012) for more details on the AMBHAS model. The decision model describes farmers' decisions and practices on their farms. Meaningful model integration requires calibration and validation of the global model and consistency in the underlying system boundaries, assumptions and scale of analysis of these diverse models in the NAMASTE model. As Kling et al. (2016) suggested, it is necessary to develop "bridge" models that convert outputs of one model into inputs of another. This approach enables atomic models to be connected at different scales and to operate together by downscaling outputs from watershed to field models. As an example the BOREWELL model is considered as a "bridge" model to convert the groundwater level which is a watershed output from the AMBHAS model to the available water for irrigation at the plot scale which is a field data used as an input for the field model STICS and by upscaling outputs from field to watershed models (e.g. outputs on drained water from the atomic STICS models and pumped water from the atomic BOREWELL models are used by the "bridge" model NET RECHARGE to compute the daily net recharge at the watershed scale that will be used as input by the watershed model AMBHAS). This can ensure that component models are manageable and provide outputs at both field and watershed scales (Hibbard and Janetos, 2013). Work on hard-linked integration is still on-going. Soft-linking is a necessary starting point to test different

Table 1
Description of farmers' activities in terms of time window, needed resources and date.

Activities	Plots/crop	Time window	Needed resources	Date of the activity
1st tractor plough	F1P1/0.9 ha of turmeric	1st to 15th of March	1 tractor and 3 male laborers	March, 10th
	F1P2/0.1 ha of marigold	1st to 15th of March	1 tractor and 1 male laborer	March, 15th
	F2P1/1.6 ha of turmeric	1st to 15th of March	1 tractor and 5 male laborers	March, 11th
	F2P2/0.4 ha of marigold	1st to 15th of March	1 tractor and 1 male laborer	March, 16th
2nd tractor plough	F1P1/0.9 ha of turmeric	7th to 23rd of March	1 tractor and 3 male laborers	March, 21th
	F1P2/0.1 ha of marigold	7th to 23rd of March	1 tractor and 1 male laborer	March, 23th
	F2P1/1.6 ha of turmeric	7th to 23rd of March	1 tractor and 5 male laborers	March, 20th
	F2P2/0.4 ha of marigold	7th to 23rd of March	1 tractor and 1 male laborer	March, 22th
1st bullock plough	F1P1/0.9 ha of turmeric	14th to 30th of March	1 pair of bullock and 3 male laborers	March, 28th
	F1P2/0.1 ha of marigold	14th to 30th of March	1 pair of bullock and 1 male laborer	March, 30th
	F2P1/1.6 ha of turmeric	14th to 30th of March	2 pairs of bullock and 5 male laborers	March, 28th
	F2P2/0.4 ha of marigold	14th to 30th of March	1 pair of bullock and 1 male laborer	March, 30th
2nd bullock plough	F1P1/0.9 ha of turmeric	21th of March to 7th of April	1 pair of bullock and 3 male laborers	April, 4th
	F1P2/0.1 ha of marigold	21th of March to 7th of April	1 pair of bullock and 1 male laborer	April, 9th
	F2P1/1.6 ha of turmeric	21th of March to 7th of April	2 pairs of bullock and 5 male laborers	April, 4th
	F2P2/0.4 ha of marigold	21th of March to 7th of April	1 pair of bullock and 1 male laborer	April, 9th
3rd bullock plough	F1P1/0.9 ha of turmeric	none	none	
	F1P2/0.1 ha of marigold	28th of March to 30th of April	1 pair of bullock and 1 male laborer	April, 26th
	F2P1/1.6 ha of turmeric	none	none	
	F2P2/0.4 ha of marigold	28th of March to 30th of April	1 pair of bullock and 1 male laborer	April, 26th
Sowing	F1P1/0.9 ha of turmeric	22th of March to 1st of May	5 male and 9 female laborers	April, 13th
	F1P2/0.1 ha of marigold	22th of March to 1st of May	1 male and 1 female laborers	April, 27th
	F2P1/1.6 ha of turmeric	22th of March to 1st of May	10 male and 16 female laborers	April, 13th
	F2P2/0.4 ha of marigold	22th of March to 1st of May	1 male and 2 female laborers	April, 27th
1st fertilization	F1P1/0.9 ha of turmeric	1 to 5 days after sowing	2 male and 1 female laborers	April, 18th
	F1P2/0.1 ha of marigold	1 to 5 days after sowing	1 male and 1 female laborers	April, 29th
	F2P1/1.6 ha of turmeric	1 to 5 days after sowing	3 male and 2 female laborers	April, 18th
	F2P2/0.4 ha of marigold	1 to 5 days after sowing	1 male and 1 female laborers	April, 29th
2nd fertilization	F1P1/0.9 ha of turmeric	30 to 40 days after sowing	2 male and 1 female laborers	May, 31st
	F1P2/0.1 ha of marigold	30 to 40 days after sowing	1 male and 1 female laborers	May, 31st
	F2P1/1.6 ha of turmeric	30 to 40 days after sowing	3 male and 2 female laborers	May, 31st
	F2P2/0.4 ha of marigold	30 to 40 days after sowing	1 male and 1 female laborers	May, 31st
3rd fertilization	F1P1/0.9 ha of turmeric	60 to 80 days after sowing	2 male and 1 female laborers	July, 2nd
	F1P2/0.1 ha of marigold	none	none	
	F2P1/1.6 ha of turmeric	50 to 60 days after sowing	3 male and 2 female laborers	July, 2nd
	F2P2/0.4 ha of marigold	none	none	
1st weeding	F1P1/0.9 ha of turmeric	10 to 35 days after sowing	8 male and 21 female laborers	April, 28th
	F1P2/0.1 ha of marigold	5 to 15 days after sowing	1 male and 1 female laborers	May, 2nd
	F2P1/1.6 ha of turmeric	10 to 35 days after sowing	14 male and 37 female laborers	April, 29th
	F2P2/0.4 ha of marigold	5 to 15 days after sowing	1 male and 2 female laborers	May, 2nd
2nd weeding	F1P1/0.9 ha of turmeric	55 to 65 days after sowing	8 male and 21 female laborers	June, 11th
	F1P2/0.1 ha of marigold	30 to 45 days after sowing	1 male and 1 female laborers	May, 30th
	F2P1/1.6 ha of turmeric	55 to 65 days after sowing	14 male and 37 female laborers	June, 10th
	F2P2/0.4 ha of marigold	30 to 45 days after sowing	1 male and 2 female laborers	May, 30th
3rd weeding	F1P1/0.9 ha of turmeric	85 to 95 days after sowing	8 male and 21 female laborers	July, 15th
	F1P2/0.1 ha of marigold	none	none	
	F2P1/1.6 ha of turmeric	85 to 95 days after sowing	14 male and 37 female laborers	July, 16th
	F2P2/0.4 ha of marigold	none	none	
4th weeding	F1P1/0.9 ha of turmeric	115 to 125 days after sowing	8 male and 21 female laborers	August, 13th
	F1P2/0.1 ha of marigold	none	none	
	F2P1/1.6 ha of turmeric	115 to 125 days after sowing	14 male and 37 female laborers	August, 12th
	F2P2/0.4 ha of marigold	none	none	
Irrigation	F1P1/0.9 ha of turmeric	1 to 240 days after sowing/minimum 2 irrigations/maximun 16 irrigations	1 male laborer	April, 13th/May, 11th/May, 22nd/ June, 2nd/June, 13th/June, 24th/ July, 5th/July, 16th/July, 27th/ August, 7th/August, 18th/August, 29th/ September, 9th/September, 20th/ October, 1st
	F1P2/0.1 ha of marigold	none	none	
	F2P1/1.6 ha of turmeric	1 to 240 days after sowing/minimum 2 irrigations/maximun 12 irrigations	2 male laborers	April, 13th/May, 11th/May, 22nd/ June, 2nd/June, 13th/June, 24th/ July, 5th/July, 16th/July, 27th/ August, 7th/August, 18th/August, 29th
	F2P2/0.4 ha of marigold	none	none	
Harvest	F1P1/0.9 ha of turmeric	240 to 300 days after sowing	20 male and 23 female laborers	November, 26th
	F1P2/0.1 ha of marigold	85 to 100 days after sowing	2 male and 3 female laborers	August, 19th
	F2P1/1.6 ha of turmeric	240 to 300 days after sowing	35 male and 42 female laborers	November, 27th
	F2P2/0.4 ha of marigold	85 to 100 days after sowing	8 male and 10 female laborers	August, 19th

modelling and linking approaches (Holz et al., 2016). It ensures practicality, transparency, and learning with low initial investments in computer programming. Future work on hard-linking will ensure efficiency, scalability, and control with automatized exchanges of information between models.

In this study, operational validation was performed mainly by

subjectively and qualitatively exploring model behavior (Sargent, 2013). We developed a simulation model able to reproduce interactions between decisions (investment and technical) and processes (resource management and biophysical) under scenarios of climate-change, socio-economic and water-management policies. Nonetheless, quantitative simulation results for the Berambadi case study still have high uncertainty due to, for instance, simplification of some biophysical processes, simplification due to the farmers' typology or simplification due to the grid of climate. Calibrating and validating the NAMASTE model is an important and time-consuming step that is still underway (94 parameters are directly accessible in the coupled model, and AMBHAS and STICS have many internal parameters that require tedious calibration).

In our experimental model, we simulated a virtual village composed, we simulated a virtual village composed of two virtual farms that have access to groundwater in the same AMBHAS cell. The watershed scale of the AMBHAS model was not used and considering only one cell of this model resulted in simplifying the watershed model by ignoring lateral water fluxes. Thus, our model is still considered as a dynamic model for water management at the farm level and cannot be considered yet as an agent-based model. In future work, we will consider the upscaling issue from the perspective of modeling the consequences of farmers' adaptations to changes in climate and groundwater. Upscaling from the farm level to watershed, regional and national levels is a common approach for studying system behavior and dynamics, such as farm adaptations to climate change (Gibbons et al., 2010), land use and land cover changes in response to climate change (Rounsevell et al., 2014) and ecosystem changes in response to biotic and abiotic processes (Nash et al., 2014). Peters et al. (2007) identified three types of scales: “fine” (one individual), “intermediate” (groups of individuals) and “broad” (large spatial extents such as the landscape, region and planet). The appropriate scale is defined by the research question or hypothesis and often requires upscaling or downscaling existing models (Gibbons et al., 2010). The challenge of aggregation or upscaling is to determine which fine-scale details matter most at intermediate or broad scales. Research questions differ according to the scale. At the farm scale, we focused on farmers' decision-making processes and their adaptation to uncertain changes (e.g. climate and resource availability). The watershed level requires exploring the influence of decision making on the groundwater table rather than the process of decision making itself and to consider interactions between individuals for shared resources. At the watershed level, relative trends are more important than absolute values. For example, at the watershed level we are more interested in the total amount of groundwater used for irrigation in the watershed than on individual farms. In the agricultural literature, there are few models dealing with both watershed and individual farm scale representations. The SHADOC model (Barreteau and Bousquet, 2000), the “Bali Model” (Lansing and et Kremer, 1994) and the SINUSE model (Feuillette et al., 2003) simulate water management at the watershed scale but are limited to a single scheme scale or to management units that are not the individual farmer but farmers irrigation groups or a villages interacting in use and management of the resource with decision-making processes based on maximisation functions of farmers' (or groups' or villages') incomes according to their available resources. The multi-agent MAELIA's (Gaudou and Sibertin-Blanc, 2013) and CATCHSCAPE's (Becu et al., 2003) architectures aimed at being integrative, spatially distributed and individual-based in order to cope with complex and adaptive issues at the watershed scale. In future work, our upscaled model will provide a detail description of the farmer cognitive agents with decision-making processes and adaptive behavior.

Our model provides tools to analyze, evaluate, and optimize agronomic, environmental and economic criteria. We tested the model with a baseline scenario to simulate current farming practices in the Berambadi watershed and predict influence of the latter on groundwater level in a virtual village composed of two farms. Modeling agricultural production scenarios can help stakeholders make decisions about regulations and resource restrictions and encourage new practices to recommend to farmers.

6. Conclusion

We developed an original simulation model of a farming system that combines relevant principles highlighted in the scientific literature. The model was initially developed to address critical issues of groundwater depletion and farming practices in a watershed in southwestern India. Its structure, frameworks and formalisms can be applied to other agricultural contexts. Our application focused on water management in semi-arid agricultural systems, but the model can also be applied to other farming systems to confirm the reusability and robustness of the framework.

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